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| Intelligent Recommendation Service |
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| Implementation Report |

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# Introduction

With the growing emergence of online content as a service, there is need for the implementation of an Intelligent Recommendation Service, which will allow the company to increase their revenue, by being able to recommend their products to customers using gained knowledge regarding their interests. The program outlined in this report aims to meet the goals and exceed client expectations with capability to enable the comparison of song features through a wide range of similarity metrics and the ability to provide recommendations based on a target entry. The system does this through successful reading of the file structure, appropriate assignment through suitable data structures and implementation of suitable libraries, alongside key comparison of suitable features collected from the provided data.

# Problem Analysis

To create the solution, the problem needs to be broken down into steps. The steps needed for this implementation are as follows.

1. Reading of the music dataset file
2. Searching artists and songs
3. Computing Similarity between artists / music tracks by ID
4. Generating recommendations to a user based on their target input

To accomplish these steps, it is important to analyse the problem before deciding on the approach to take. There are also a variety of other things to consider when thinking about the best way to approach the problem. One of the problems involved in a Recommendation Service is new users. It’s the aim of the service to provide something that draws in new users, but the problem of recommending songs to a new user is that their tastes in music are not existent on the system. To understand the taste of the user, it is important for the program to be subjective and not recommend many things to a user until there is more data to make use of, so the algorithm can be accurate in its assumptions. It can also be a good idea to recommend songs to a user to see what the response would be.

The steps defined above showcase the overall direction of the implementation of the system, and the stages that must be considered when planning the implementation documents. Notably, there is no avenue for a user, new or existing, to search for songs within the dataset. There needs to be an avenue to allow the user to be able to search by name or closest match. The metrics to be created for the similarity scoring need to be tested for suitability of purpose, as not all metrics will be useful, but having some variety to choose from is never a bad option either. Generating recommendations for the user also depends on their target, and there are a few different types of recommendation styles that can be used. In this case, the program uses Content Based Filtering, which takes a target from the user and generates recommendations based on this target in real time.

# Solution Requirements

This section outlines the characteristics of the solution, and how these characteristics enable the program to meet the needs of the stakeholders and the business.

## Functional Requirements

When considering the functional requirements, there are a few aspects that are key for this program. The most important of these is the **user requirements**, which can be showcased in a use case diagram (see appendix). This style of diagram helps to show what the program does and how this meets the requirements of the user. This highlights what the program does and how it meets what the user would be expecting when they are using the program.

Another important requirement to consider is the **system requirements**. For this program, the system requirements are small. The main requirement to run the program is a system that can access Python and run a python notebook in the environment of their choice. This could be through Jupyter Notebook or Visual Studio Code using the python add-on, as the system uses a simple UI for a simple program with effective ease of use, including some modular flexibility. An important thing to note here is that the modules that need to be imported must remain in the same folder as the solution, as not to break functionality.

## Non-functional Requirements

The non-functional requirements aim to define the system behaviour. This section discusses these requirements and how they must be met when creating the solution.

The non-functional requirements have been listed in this section. The first is **Usability**, which refers to how easy the program is to use for an end user. The program will use a simple UI, which will require input from the user in the form of text entry. The use of this simple UI for the program input makes the solution efficient, intuitive and maintains a low perceived workload. There are plenty of text outputs for the user so that they understand and can easily follow along and input the relevant response to successfully proceed within the program. Any errors are relayed back to the user in an understandable manner.

Continuing, the next requirement is **Supportability**, which refers to how easy it is to update the codebase when required. The system will make use of Object-Oriented Programming principles with the aim to make the codebase as compact as possible. Making use of OOP allows for the program to eliminate need for unnecessary code duplication in places by making use of Inheritance to share methods from one class to another. Good use of code structure that follows coding standards and contains useful comments will allow a future developer to be able to refresh and update the code when and if necessary.

Another consideration is **Appropriateness**, which is the suitability of the program for its intended purpose. This requirement is simply a measure of how well the program meets its intended purpose, which is to recommend songs or artists to a user based on what they already like. Successful implementation of the program will allow it to meet this requirement without any issue.

The program also needs to be **Reliable**. This involves the effective use of exception handling, which makes sure that the program doesn’t experience any crashes if the user inputs a value that would normally create an error, such as when a data frame is called when it is not yet instantiated. The program will therefore make effective use of built-in exception handling to catch all exceptions in the program, and instead of crashing, will print a message to the user, and then re-run the section of the program that was interrupted due to an error if appropriate.

The last non-functional requirement is **Performance**. The program runs through a single execution that calls multiple modules through various sections of the UI. This makes performance of the program fast; the lightweight nature of the implementation will allow the program to run fast and snappy when being used. While there is no need for the program to run fast, the nature of the implementation makes a fast-running program easy to accomplish. The slowest aspect of the program is when the user enters their target, and the program calculates the metric of the target against the library to find recommendations.

# Implementation of Solution

This section outlines the steps taken to accomplish program implementation. More thorough discussion regarding the execution of the program can be found in later sections.

The implementation of the program was an incremental process, which involved working in steps to complete sections of the codebase and returning if any issues came up on previously completed sections. Use of GitHub for saving work and creating issues helped to gauge progress. To accomplish the file loading, the Python library Pandas was used within a file loader class. Using this library meant that all encoding and splitting of data was done automatically using a comma as the delimiter.

Three Classes are used to split up the data as Artist, Song and Extras, where the artist name is included in the Artist class, the song features used for comparison alongside the song name are within the Song class, and the extra features of the data that are not used are within the Extras class. A Track class uses Multiple Inheritance to inherit all the keyword arguments and methods from these three classes and use them to create a combined class for the entire dataset. User searching and the search function are included in final implementation, which helps if the user doesn’t know the necessary ID. As the program takes an ID number as the input, if the user doesn’t know the ID, then the search function will help them to find it, to pull the information for comparison or recommendation.

A method was created within the Track class to return a data frame to be used later for calculations. Functionality to present the number of successful matches within artist and song searches, allows user feedback regarding the accuracy of their search, and then presents them with a box asking them if they want to view the results. This is done so that when a user conducts a search, the program doesn’t simply throw all the results at the user without some sort of feedback beforehand. The user also can simply reject the search results and move on in the program. Searching for a song can be done infinitely until the user has had enough and wishes to proceed, this adds flexibility and some modularity to the solution.

Creation of the metrics was done through method creation and use of the NumPy and SciPy libraries to extract the metric functions needed, which were then called using dot notation. The overall functionality of the similarity functions includes error checking to avoid incorrect input, when the same numerical ID is entered, the program will output 1 for comparison, alongside the ability to reset the program if a feature was entered that couldn’t be found. Once all metric functions were created and checked for errors, the recommendation class was created.

The recommendation class was created using inherited properties from the Similarity metric class which housed the metrics to be used. A choice method is also created to define the metric to be used, as some of the metrics require the sorted results to be reversed and some don’t, so this needs to be specified in the code to avoid presenting false results to the user. To keep the data to a similar scale, a scaler function is used called a MinMaxScaler which normalises all the values within the data before transformation occurs to turn the data into an array. This is done because doing calculations on a data frame took a long time, and the array turned out to be much shorter in this respect.

There is the issue of the program returning the same song / artist/s that are being sent as the target, which is corrected by removing the target from the library before any recommendations can be calculated. The algorithm is chosen by the user and then the program takes the target and loops through the library, using this metric on the target v every individual vector within the array before returning a set of the n closest results to the target, where the n value is chosen by the user as a multiple of 5, with 5 being the lowest value accepted.

To test against this implementation, the K Nearest Neighbor algorithm, the distance section of the classifier is used as a sole function due to the inability to use the full classifier for this task. By measuring the accuracy of the results obtained from the created solution against the algorithm, it is possible to see that for most of the results, the order of results is mostly in the same order, with the occasional difference being observed between the two solutions. …TODO expand on this after meeting…

# Program Execution

This section discusses the implementation and execution of the program through the main notebook. The section focuses on the choices made and the structural decisions when deciding upon program flow and flexibility.

…TODO complete this section… / can’t be done until UI is finished

# Personal Reflection

This section provides an overview of the main issues found within the program during implementation and outlines the ways that they were corrected where necessary. The section mainly discusses the implementation of the two modules for the program, and the implementation of the main notebook.

## Dataset Loading

Loading the data is the first part of the implementation. Working with the file was seamless whilst making use of Pandas. The use of zip allowed the data to be added to the class Track as a class-based instance, which essentially made the file a dictionary with additional functionality. Indexing is done automatically by Pandas, so this wasn’t required of myself. IDs are present in searches by the user for songs or artists.

## Similarity Metrics

The program uses 5 similarity metrics to run comparisons on features and generate recommendations. These metrics are Euclidean, Manhattan, Pearson Correlation, Cosine and Jaccard. When working with these metrics, it was increasingly important that rigorous testing was conducted to make sure that there were no issues regarding inputs, outputs, and calculations of the results. The premise of comparisons is a value against another value, whilst recommendations work by taking a target set of values and comparing them to all other values for each other item in the library. A problem that arose in using two features of shape (1, ) is that Pearson Correlation (PC) cannot be used in this respect. This is because a correlation requires at least two x values and two y values to make a prediction of correlation and output an accurate result. When using correlation for recommendations however, no issues were discovered.

Euclidean and Manhattan are successful for comparing and recommending items for a user, as these algorithms work by taking the first item from the second and applying some other math to the results to make them differ form one another. Comparisons done with these two metrics shared the same result, but for recommendations, these results were no longer identical in score. Euclidean and Manhattan are accurate across all values, leading to a successful implementation of these metrics. The same can be said for the metrics of Cosine and Jaccard, where the issues found when working with these metrics were small, although Jaccard is not a suitable metric for this task, as most of the time the output is 0 or 1, and is not very informative, due to what Jaccard is aiming to tell the user about the values they are inputting.

## Generating Recommendations

When deciding on the best approach for generating n recommendations, the first initial thought was to adapt the solution used when the program compares all features from an item against another item. Creating a target variable and taking a feature and looping through all items and doing the calculation on this value against all other items was successful, but the results were not as accurate as they could be. To further expand and improve upon this solution, it was decided to take the id number of an item and loop through all other items and do the metric calculation of all features of an item against all other items instead to generate a more accurate recommendation engine.

The use of a data frame to implement this was initially very slow, due to the dimensionality of the data. Instead, using a scaler to normalise all values into an array, and then calculate similarity proved to be incredibly fast in comparison, with the slowest result taking 10 seconds using Pearson Correlation. Once these results were compiled and added to a list, they were sorted by their scores and then the IDs of the ordered results were used to pull the names and print them to the user. The use of the class-based list from file loading proved incredibly useful for this. The loop to print results to the user will then terminate when the number of printed results reaches the value of the n that the user enters.

## Main Function

…TODO when UI is complete…

# Evaluation

# Conclusion

# References

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# Appendix

### Program Structure Flowchart

The flowchart that shows the overall expected flow of the program is found here, provided below. A small label has been added to the right side of the flow-chart, so that a reader can understand what ID refers to here if they are not sure.

### System Architectural Diagram

### Use Case Textual Diagram

|  |  |  |
| --- | --- | --- |
| Actors | Use Cases | Description |
| User | Search Artist | Query the Class-Library |
| Search Song | Query the Class-Library |
| Enter IDs | IDs to be used for Comparison |
| Choose Metrics | Metric choice to compare features |
| Artist v Artist Dictionary Creation | Invoke the function |
| Rate Music | Convey liking of Music (not included) |
| Admin | Calculate Similarity | Invoke the chosen function |
| Show Predictions | Recommendation Scores |
| Gather Search History Data | Log user activities (search history) |

### Class Diagram

### Pseudocode

#### Load dataset module

#### Similarity module

#### Main Notebook

### Requirement Testing Matrix

TODO-refine to match Assignment 2

|  |  |  |
| --- | --- | --- |
| **Requirement** | **Use Case** | **Response** |
| User can choose artist or song | Enter artist and song | Program proceeds |
| Enter invalid entry | Program complains and asks if user wants to quit |
| Artist Searching | Does user want to compare?  User enters ‘yes’ | Program continues, starts artist comparison |
| Does user want to compare?  User enters ‘no’ | Program continues, prompts the user regarding artist searching |
| User enters a correct name | Program prints search results, prompt for the user |
| User enters an invalid name | Program prints that there no results |
| User enters an invalid entry | Program prints a message, starts the metric compare section |
| Song Searching | User wants to search for a song | Song searching begins |
| User enters an invalid entry | Program restarts |
| User enters a word | Searching finds songs with the matching word |
| User enters multiple words | Searching finds songs with any of the entered words  **Needs refinement!** |
| User enters numbers or symbols | Searching returns matches |
| User enters ‘no’ | Metric selection begins |
| Metric Selection | User enters a correct number from the list provided | Expected Metric function runs |
| User enters a character | Program restarts |
| User enters an invalid number | Program states entry is wrong, asks the user to retry |
| Entering IDs for features | User enters two correct IDs  These IDs match | Program complains, asks the user to enter two IDs again as the IDs can’t match |
| User enters two correct IDs  These IDs don’t match | Program asks for the feature |
| User enters a character | Program prints an error message and ends, **could be refined** |
| User enters a number bigger than the size of the list | Program says the feature is wrong, could refine the error message, but functionality is as expected |
| Feature Input | User enters a valid feature from the list provided | Output the similarity score |
| User enters an invalid feature, number or otherwise | Program tells the user that the feature doesn’t exist |
| User enters ‘no’ or nothing | Output all features similarity scores |
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